FairGAN: GANs-based Fairness-aware Learning for Recommendations with Implicit Feedback

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ABSTRACT

Ranking algorithms in recommender systems influence people to make decisions. Conventional ranking algorithms based on implicit feedback data aim to maximize the utility to users by capturing users' preferences over items. However, these utility-focused algorithms tend to cause fairness issues that require careful consideration in online platforms. Existing fairness-focused studies does not explicitly consider the problem of lacking negative feedback in implicit feedback data, while previous utility-focused methods ignore the importance of fairness in recommendations. To fill this gap, we propose a Generative Adversarial Networks (GANs) based learning algorithm *FairGAN* mapping the exposure fairness issue to the problem of negative preferences in implicit feedback data. *FairGAN* does not explicitly treat unobserved interactions as negative, but instead, adopts a novel *fairness-aware learning strategy* to dynamically generate *fairness signals*. This optimizes the search direction to make *FairGAN* capable of searching the space of the optimal ranking that can fairly allocate exposure to individual items while preserving users' utilities as high as possible.

CCS CONCEPTS

• **Information systems** → **Recommender systems**.

KEYWORDS

Fairness, Ranking, Exposure, GANs, Recommendation

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1 INTRODUCTION

Recommendations based on implicit feedback data have been gaining attention from both researchers and practitioners, and most of these recommendation algorithms aim to maximize the average utility to users by capturing users' preferences over items [11, 41, 42]. However, these utility-focused algorithms tend to cause fairness issues that require careful consideration in online platforms [31, 43]. The exposure of items is closely related to the interests of the item providers, such as the revenue from product sales and the job opportunity candidates can gain, etc. The competitive relationship between items requires a fair way to allocate the exposure of items to users. Unfair allocation-of-exposure of items can cause the Matthew effect [4, 5, 7, 32], which means that high-ranked items are more likely to gather additional feedback to influence future rankings and gain more and more user attentions, while low-ranked items will be marginalized gradually. While there are existing research on this issue, they mostly focus on studying how to fairly allocate exposure to items [34, 37, 52], well-known examples include the approach [34] that re-ranks the ranking to guarantee a minimum exposure of individual items given relevance scores of items, an adversarial learning-based method [52] that enforces relevance scores distribution between item groups to be similar based on a given recommendation model, and a linear programming algorithm that takes group fairness as an optimization constraint [37].

Besides the fairness issue, there is another challenge in the context of implicit-feedback based recommendations: how to extract *negative signals* from the unobserved interactions, since unobserved interactions are the mixture of negative interactions (i.e., the user does not like the item) and unlabeled positive interactions (i.e., the user is unaware of the item) [2, 3, 15, 16]. Many existing recommendation models based on implicit feedback data mainly employ two learning strategies: (i) *heuristic*: treating all unobserved interactions as negative and assigning an uniform lower confidence on them [13, 14, 26]; (ii) *sampling*: determining which unobserved interactions are sampled and treated as negative to update model parameters [1, 11, 25, 36, 42, 46]. However, these methods only focus on maximizing user utilities and ignore the importance of the fairness in recommendations.

To fill the gap between existing research focusing on fairness issues and methods focusing on the problem of lacking negative feedback, (i.e., the former do not explicitly consider the challenge of implicit feedback while the latter do not consider the fairness issues), we consider mapping the exposure fairness issue to the problem of lacking negative feedback in implicit feedback data in this paper. Specifically, we do not explicitly treat unobserved samples as negative, but instead, propose a novel learning strategy *fairness-aware learning strategy* to search the space of the ranking

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that can fairly allocate exposure across individual items while maintaining users' utilities as high as possible. With this novel learning strategy in mind, we propose a novel Generative Adversarial Networks (GANs) [21] based learning algorithm, called *FairGAN*. It consists of two components: one is called *ranker*, which first models user preferences only from observed interactions; the other is called *controller*, which captures the distribution of items' exposures according to the current ranking generated by the ranker in each iteration dynamically. With the captured exposure distribution in hand, the controller generates and supplies *fairness signals*, that enforce exposure of individual items to be equal, to the ranker for searching the space of the optimal ranking that can fairly allocate exposure to items, and maintain users' utilities as high as possible. The ranker then dynamically adapt generated rankings in each iteration based on the *fairness signals* offered by the controller, eventually generating rankings that can fairly expose items to users and retain the high users' utilities. The proposed controller is capable of generating various *fairness signals* based on different fairness objectives [8, 18, 37, 38, 48] for satisfying different fairness criteria, regardless of whether the objectives are differentiable or not.

In summary, our contributions are as follows: (i) The first GANs-based learning algorithm *FairGAN* mapping the exposure-based fairness issue to the problem of lacking negative feedback in implicit feedback data, which adopts a novel *fairness-aware learning strategy* that does not explicitly treat unobserved interactions as negative, but instead generates *fairness signals* to search the space of the optimal ranking that can fairly allocate exposure to items and preserve users' utilities as high as possible; (ii) A flexible fairness controller being able to generate various *fairness signals* for the ranker based on both differentiable and non-differentiable fairness objectives for satisfying different fairness criteria; (iii) Extensive experiments on four real-world datasets show that *FairGAN* outperforms the state-of-the-art state-of-the-art methods, including utility-focused methods, and the fairness-aware methods.

2 RELATED WORK

Exposure Fairness in Ranking: Due to the ubiquitous application of ranking systems, many recent works have been concerned about exposure fairness in rankings [18, 31, 34, 37, 38, 47, 48, 52]. In [37], the authors formulate the exposure of items and propose a computational framework applying linear programming algorithm to post-process result ranking based on three forms of group fairness optimization constraints. Yang and Stoyanovich [47] minimize the difference of distributions of item exposure among different groups by a regularization. In [31], the authors propose the first dynamic learning to rank algorithm that overcomes rich-get-richer dynamics while enforcing a configurable allocation-of-exposure scheme. A post-processing method is proposed in [34] to re-rank given ranking to enforce each item to at least satisfy a minimum exposure opportunity. However, all these previous approaches pay only attention to how to fairly allocate exposure of items and neglect the problem of lacking negative feedback that originates from the one-class implicit feedback data [16] in Top-k recommendations. In this work, we consider mapping the fair allocation-of-exposure issue to the problem of lacking negative feedback in implicit feedback data. The proposed *FairGAN* is able to address these two crucial issues simultaneously by a novel *fairness-aware learning strategy*.

Recommendations in Implicit Feedback: Implicit feedback reflecting natural behaviours (e.g., purchases, clicks) of users is widely used in recommender systems since it's easier to collect. However, such one-class data only provides a partial signal of positive feedback, and unobserved user-item interactions are the mixture of negative feedback (i.e., the user does not like the item) and unlabeled positive feedback (the user is unaware of the item) [16]. Many efforts have been made to address this issue, well-known examples include *heuristic*-based methods [13, 14, 26, 29] and *sampling*-based methods [1, 11, 36, 42, 45, 46]. Efficient Neural Matrix Factorization (ENMF) [14] is a *heuristic-based* method that treats all missing entries in implicit feedback data as negative feedback of users and assigns smaller confidence on unobserved data during learning. Bayesian Personalized Ranking (BPR) [36] is a pairwise method using *sampling-based* learning strategy that assumes that observed user-item interactions should be ranked higher than sampled unobserved counterparts. Other well-known neural-based methods based on the *sampling-based* learning strategy apply the uniform negative sampler to uniformly select unobserved interactions and treat them as negative. However, all existing methods only focus on maximizing user utilities and ignore the importance of the fairness in recommendations. In this paper, we propose a *fairness-aware learning strategy* that does not explicitly treat unobserved interactions as negative but instead generates *fairness signals* to search the space of the fair rankings with high utility.

GANs-based Recommender Systems: Generative Adversarial Networks (GANs) [21] is a combination of a generative model (shortly, G) and a discriminative model (shortly, D). Through the continuous confrontation game between G and D, G can finally mimic the distribution of ground truth under the guidance of D. An increasing number of researchers are attracted to migrate the GANs' success in several domains [9, 17, 23, 28, 39] to recommender systems [11, 12, 40, 42, 44, 51]. For example, IRGAN [42] opened up a new path for research of GANs in information retrieval (IR) and recommendation systems. In IRGAN, G samples indices of relevant items for users, and D learns to discriminate the ground truth items from the generated items by G. CFGAN [11] introduces a vector-wise adversarial training method that regards each user purchase vector as a training instance to completely exploit the advantage of Conditional GANs [30] to generate higher recommendation quality in collaborative filtering (CF). These existing approaches all achieved significant improvements on recommendation quality by the sampling-based learning strategy that employs a uniform negative sampler to randomly select unobserved data from implicit feedback data. However, these approaches neglect the consideration of fairness issues. Distinct from existing works, in this paper we apply the proposed *fairness-aware learning strategy* based on the more stable Wasserstein GANs [6] with a gradient penalty [22] to train the ranker and controller in the proposed *FairGAN*, eventually generating fair rankings with high user utilities.

3 PROBLEM STATEMENT

Here, we state the problem of optimal rankings that can fairly allocate exposure to users while preserving high users' utilities. Let $\mathcal{U}$ and $\mathcal{I}$ be sets of users and items respectively, where $|\mathcal{U}| = m$

and $|\mathcal{I}| = n$, and we use the index u to denote a user, and v to denote an item. Let $\mathbb{R} = [r_v^u]^{m\times n} \in \{0,1\}$ be the user-item data matrix to indicate whether u has purchased or clicked on item v. $\mathcal{R}$ is denoted as the set of observed entries in $\mathbb{R}$, i.e., non-zero values of $\mathbb{R}$. In implicit data, the user-item interactions $\mathbb{R}$ is defined as:

$$r_v^u = \begin{cases} 1, & \text{if interaction (user } u\text{, item } v\text{) is observed,} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

where 1 represents an interaction between user u and item v, indicating a positive instance that u likes v, while 0 does not necessarily mean u does not like v, it is likely that u is not aware of v.

Considering a scoring function f parameterized by θ that maps user and item features to $\mathbb{R}$, each entry r_u^v of $\mathbb{R}$ is estimated by: $\hat{r}_v^u = f(u, v|\theta)$. The Top-k recommendation problem is formulated as estimating the scoring function f for ranking items. We use π_k^u to denote the recommendation list of Top-k items for user u by decreasing the scores that are estimated by f on all items of user u: $\pi_k^u = [\arg\text{sort}_{v\in I} f(u, v|\theta)]_k$.

The utility that user u gained from the ranking π_k^u is denoted as $\tilde{U}(\pi_k^u)$, while the unfairness of items over all users is denoted as $Unf(\pi_k)$, where π_k is the set of recommendation lists of Top-k items over all users. We formulate the problem of the optimal rankings as an optimization problem in this paper:

$$\arg\max_{\theta} \tilde{U}(\pi_k), \tag{2}$$

where $\tilde{U}(\pi_k) = \sum_{u\in\mathcal{U}} \tilde{U}(\pi_k^u)$. We consider first searching the space of the optimal parameters θ to induce the optimal rankings π_k that can maximize $\tilde{U}$. And then we consider minimizing the unfairness between items in ranking π_k:

$$\arg\min_{\theta} Unf(\pi_k). \tag{3}$$

To solve this optimization problem, we first define the utility $\tilde{U}(\pi_k^u)$ of user u, and then formulate the unfairness $Unf(\pi_k)$ across items over all rankings.

3.1 User Utility

The relevance scores of recommended items can be used for deriving the utility that users gained from rankings. The utility of user u can be commonly defined as the ranking metric Normalized Discounted Cumulative Gain (NDCG) [27] over the ranking π_k^u:

$$\tilde{U}(\pi_k^u) = \frac{DCG(\pi_k^u)}{DCG(\pi_k^{u*})}, \tag{4}$$

where $DCG(\cdot) = \sum_{v\in I} \frac{2^{r_v^u}-1}{log(1+rank(u,v|\cdot))}$ for user u, π_k^{u*} is the expected optimal ranking for user u, $rank(u, v|\cdot)$ is the position that item v is placed at in the ranking $\cdot$ for user u.

3.2 Exposure-based Fairness

We consider the exposure-based fairness issue across individual items. Following the previous works [18, 31, 37, 48], we first define the exposure of item v over the rankings π_k:

$$Exp(v|\pi_k) = \frac{1}{m}\sum_{u\in\mathcal{U}} b_v^u, \tag{5}$$

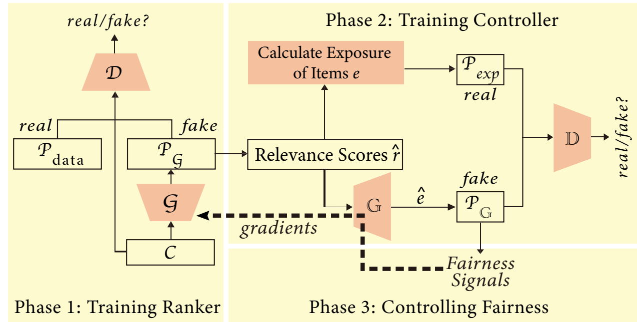


Figure 1: The Structure of *FairGAN*.

where b_v^u is a position bias indicating the relative importance of the position that item v is placed at in Top-k ranking π_k^u of user u. We set it to the standard definition in DCG [27] if v is recommended to u, and 0 otherwise:

$$b_v^u = \begin{cases} \frac{1}{log(1+rank(u,v|\pi_k^u))}, & \text{if } v \in \pi_k^u, \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

With the definition of exposure of items in hand, we can define the unfairness $Unf(\pi_k)$ of individual items as the Individual Exposure Disparity (IED).

Definition 1. ***Individual Exposure Disparity*** *Individual exposure fairness holds when any pair of items maintain the same exposure to users. For minimizing the disparity between any pairs of individual items, we invoke the Gini coefficient [19] which is commonly used for measuring the pairwise disparity, thus the Individual Exposure Disparity of π_k (IED) is denoted as:*

$$IED = \frac{\sum_{v,v'\in\mathcal{I}} |Exp(v|\pi_k) - Exp(v'|\pi_k)|}{2n\sum_{v''} Exp(v''|\pi_k)} \tag{7}$$

The value of IED is ranged from 0 to 1, where 0 expresses perfect equality that is all individual items have the same exposure, while 1 represents maximal inequality with respect to exposure among individual items. In this paper, we aim to generate a set of rankings π_k which is able to reduce the disparity IED as much as possible while preserving the high utility $\tilde{U}$.

4 *FAIRGAN*

To solve the optimization problem defined in Section 3, we propose an GANs-based solution called *FairGAN* consisting of two components (as shown in Fig. (1)), where a ranker component learns a scoring function that is to maximize utility of users and a controller component learns to provide the ranker with *fairness signals* to minimize the disparity defined in Eq.(7). There are three phases in each iteration during training *FairGAN*, (i) training the ranker to capture users preferences; (ii) training the controller to capture the current exposure distribution of items; (iii) controlling the fairness by generating fairness signals and adapting the ranker. Next, we illustrate the way to learn each component of the algorithm.

4.1 The Ranker (Phase 1)

The process of training the ranker component in *Phase 1* is shown in left area of Fig. (1). The ranker consists of a generative model (shortly, $\mathcal{G}$) parameterized by θ and a discriminative model (shortly,

$\mathcal{D}$) parameterized by Θ, which plays a minimax game. Inspired by [11], $\mathcal{G}$ and $\mathcal{D}$ in the ranker are user-conditional to take user's personalization into account. Specifically, given the condition vector $\mathbf{c^u}$ of the user u, $\mathcal{G}$ is expected to generate an n-dimensional sparse vector $\hat{\mathbf{r}}^\mathbf{u}$, where all the elements corresponding to u's purchased items $\hat{r}^u_v$ ($v \in \mathcal{R}^u$) are hopefully 1. Similarly, given the user u's conditional vector, $\mathcal{D}$ is expected to be able to distinguish the estimated purchase vector $\hat{\mathbf{r}}^\mathbf{u}$ generated by $\mathcal{G}$ from u's real one. To tackle problems of learning instability and difficulty of convergence in [11], which are inherited from original GANs, we employ the state-of-the-art variant of GANs, WGANs with a Gradient Penalty (WGANs-GP) [22] to learn $\mathcal{G}$ and $\mathcal{D}$ of the ranker. Formally, the value function of the two-player minimax game between $\mathcal{G}$ and $\mathcal{D}$ is denoted as:

$$\min_{\mathcal{G}} \max_{\mathcal{D}} \mathop{\mathbb{E}}_{r\sim P_{data}}[\mathcal{D}(r|c)] - \mathop{\mathbb{E}}_{\hat{r}\sim P_{\mathcal{G}}}[\mathcal{D}(\hat{r}|c)] - \lambda \mathop{\mathbb{E}}_{\tilde{r}\sim P_{\tilde{r}}}[(\|\nabla_{\tilde{r}}\mathcal{D}(\tilde{r}|c)\|_2 - 1)^2], \tag{8}$$

where P_{data} is the data distribution of ground truth, and $P_{\mathcal{G}}$ is the generative model distribution implicitly defined by $\hat{r} = \mathcal{G}(c)$. $P_{\tilde{r}}$ is implicitly defined for uniformly sampling along straight lines between pairs of points sampled from the data distribution P_{data} and the generator distribution $P_{\mathcal{G}}$. The key idea of the last term is that the optimal critic contains straight lines with gradient norm 1 connecting coupled points from P_{data} and $P_{\mathcal{G}}$ [22], λ is the penalty coefficient.

$\mathcal{G}$ and $\mathcal{D}$ are neural networks for optimizing the θ and Θ while minimizing and maximizing the value function, respectively. Specifically, the objective function of $\mathcal{D}$ is denoted as:

$$\max \sum_{u\in\mathcal{U}} \{\mathcal{D}(\mathbf{r^u}|\mathbf{c^u}) - \mathcal{D}(\mathcal{G}(\mathbf{c^u}) \odot \mathbf{r^u}|\mathbf{c^u}) - \lambda[(\left\|\nabla_{\tilde{\mathbf{r}}^\mathbf{u}}\mathcal{D}(\tilde{\mathbf{r}}^\mathbf{u}|\mathbf{c^u})\right\|_2 - 1)^2]\}, \tag{9}$$

where $\mathbf{r^u}$ is an indicator vector that specifies if the user u has purchased item v ($\mathbf{r^u_v} = 1$) or not ($\mathbf{r^u_v} = 0$), and $\odot$ stands for element-wise multiplication. Similarly, the objective function of generative model $\mathcal{G}$ is denoted as:

$$\min \sum_{u\in\mathcal{U}} -\mathcal{D}(\mathcal{G}(\mathbf{c^u}) \odot \mathbf{r^u}|\mathbf{c^u}). \tag{10}$$

$\mathcal{G}(\mathbf{c^u}) \odot \mathbf{r^u}$ drives $\mathcal{G}$ not to get the gradient of the loss from $\mathcal{D}$ with respect to non-purchased (unobserved) items, which is inspired by the common idea of pointwise CF models [11, 14, 26, 33] based on the observed user-item interactions. However, this would lead $\mathcal{G}$ to simply generates a purchase vector where all elements are 1 to deceive $\mathcal{D}$ [11]. To address this challenge, previous research [1, 11, 13, 14, 26, 29, 36, 42, 45, 46] treated unobserved items as not missing but zero to search the space of capturing the distribution of the real interactions. However, they do not consider the fairness issue in recommendation systems that is described in the introductory section. Distinct these existing studies, the ranker of the proposed *FairGAN* does not treat unobserved interactions as zero but is further adapted by the *fairness signals* generated by the controller. Note that the ranker is trained only on positive feedback since $\mathcal{G}$ gets only the gradients of the loss from $\mathcal{D}$ w.r.t. positive feedback. The *fairness signals* are expected to drive the ranker to be capable of searching the space of optimal rankings that can minimize the *IED* defined in Eq. (7) while capturing the distribution of the real user-item interactions as much as possible. The process of generating the *fairness signals* and controlling the fairness of the ranker based on the generated signals will be discussed in Section 4.2.

4.2 The Controller (Phase 2 and 3)

Then we detail the process of *Phase 2* and *Phase 3* shown in Fig. (1). To generate the *fairness signals* that can minimize the disparity of exposure of any pairs of items, in *Phase 2*, the controller first captures the distribution of the exposure of items based on the current presented rankings π_k derived by $\mathcal{G}$ of the ranker. In practice, the controller captures the distribution of exposure based on the rankings π_n (where n is the number of items) of all items to guarantee the *fairness signals* are capable of offering sufficient space for the ranker. Furthermore, this allows the generated *fairness signals* to guide the ranker to fairly allocate exposure in rankings of any possible length k ($1 \leqslant k \leqslant n$).

Similarly, the controller also consists of a generative model (shortly, $\mathbb{G}$) parameterized by ψ and a discriminative model (shortly, $\mathbb{D}$) parameterized by Ψ, which plays a minimax game. Specifically, $\mathbb{G}$ takes the estimated purchased vector $\hat{\mathbf{r}}^\mathbf{u}$ of user u generated by $\mathcal{G}$ as the input and outputs an n-dimentional exposure dense vector, where elements represent exposure of items v in the ranking π^u_n of user u. While $\mathbb{D}$ learns to distinguish the exposure distribution generated by $\mathbb{G}$ from the real exposure distribution calculated based on the generated scores of $\mathcal{G}$. Formally, the real exposure e^u_v of item v to user u in the ranking π^u_n is computed via $e^u_v = b^u_v$, where $v \in \pi^u_n$.

Likewise, the controller also employs WGANs-GP to learn $\mathbb{G}$ and $\mathbb{D}$. Formally, the value function of the controller is denoted as:

$$\min_{\mathbb{G}} \max_{\mathbb{D}} \mathop{\mathbb{E}}_{e\sim P_{exp}}[\mathbb{D}(e)] - \mathop{\mathbb{E}}_{\hat{e}\sim P_{\mathbb{G}}}[\mathbb{D}(\hat{e})] - \lambda \mathop{\mathbb{E}}_{\tilde{e}\sim P_{\tilde{e}}}[(\|\nabla_{\tilde{e}}\mathbb{D}(\tilde{e})\|_2 - 1)^2], \tag{11}$$

where P_{exp} is the distribution of items' exposure in rankings π_n, and $P_{\mathbb{G}}$ is the generative model distribution implicitly defined by $\hat{e} = \mathbb{G}(\hat{r})$. $P_{\tilde{e}}$ is also implicitly defined for uniformly sampling along straight lines between pairs of points sampled from P_{exp} and $P_{\mathbb{G}}$ [22]. $\mathbb{G}$ and $\mathbb{D}$ are also neural networks and optimized by the value function Eq. (11). The objective function of $\mathbb{D}$ is denoted as:

$$\max \sum_{u\in\mathcal{U}} \{\mathbb{D}(\mathbf{e^u}) - \mathbb{D}(\mathbb{G}(\hat{\mathbf{r}}^\mathbf{u})) - \lambda[(\left\|\nabla_{\tilde{\mathbf{e}}^\mathbf{u}}\mathbb{D}(\tilde{\mathbf{e}}^\mathbf{u})\right\|_2 - 1)^2]\}, \tag{12}$$

$\mathbf{e^u}$ is items exposure vector of user u, where elements are exposure of all n items to user u in the ranking π^u_n. $\mathbf{r^u}$ is generated by $\mathcal{G}$, i.e., $\hat{\mathbf{r}}^\mathbf{u} = \mathcal{G}(\mathbf{c^u})$. The objective function of $\mathbb{G}$ is as follows:

$$\min \sum_{u\in\mathcal{U}} -\mathbb{D}(\mathbb{G}(\hat{\mathbf{r}}^\mathbf{u})). \tag{13}$$

Through the adversarial learning between $\mathbb{G}$ and $\mathbb{D}$, $\mathbb{G}$ can dynamically produce exposure of individual items based on their relevance scores generated by $\mathcal{G}$ in each iteration. Assuming that $\mathbb{G}$ is optimal, the generated exposure from $\mathbb{G}$ is able to completely mimic the real exposure distribution of rankings π_n derived from $\mathcal{G}$, i.e., $\hat{e} \approx e$.

With the distribution of generated exposure $\hat{e}$ in hand, we next consider generating the *fairness signals*, in each iteration, and adapting the ranker based on them, which is *Phase 3* shown in Fig. (1). Based on the exposure-based individual fairness definition we defined in Definition 1, the rankings π_n derived from $\mathcal{G}$ are expected to have low disparity on individual items' exposure e in each iteration. However, the computation of e is not differential with respect to parameters θ of $\mathcal{G}$, we cannot directly update θ to minimize individual exposure disparity. To solve this issue, we consider optimizing π_n via the approximation of e, i.e., $\hat{e}$. Since $\hat{e}$ is generated by $\mathbb{G}$, and the relationship between $\mathcal{G}$ and $\mathbb{G}$ is straightforward, we can fix $\mathbb{G}$ and directly update θ of $\mathcal{G}$ via back-propagation by minimizing the *IED* defined in Eq. (7):

$$\min_{\theta} \alpha \cdot \frac{\sum_{v, v' \in \mathcal{I}} |\hat{e}_v - \hat{e}_{v'}|}{2n \sum_{v'' \in \mathcal{I}} \hat{e}_{v''}}, \tag{14}$$

where $\hat{e}_v$ is the summation of item v's approximate exposure in rankings π_n over all users. Through minimizing this objective, $\mathbb{G}$ generates the *fairness signals* that drives $\mathcal{G}$ to search the space of optimal rankings that can fairly allocate exposure to items while capturing the distribution of real user-item interactions as much as possible. The α is the tunable parameter controlling the trade-off between the recommendation quality and exposure disparity.

The main advantage of the controller in *FairGAN* is flexible enough to apply other different fairness objectives, including differentiable and non-differentiable ones, beyond just exposure-based fairness.

4.3 Model Training

To sum up, *FairGAN* dynamically learns the ranker and the controller of as presented rankings generate in each iteration, which takes the form of the mini-batch manner. Generally, there are three phases in each iteration during model training: (i) updating parameters θ, Θ of the generator $\mathcal{G}$ and the discriminator $\mathcal{D}$ of the ranker via Eq. (10) and Eq. (9); (ii) updating $\mathbb{G}$ and $\mathbb{D}$'s parameters ψ and Ψ via Eq. (13) and Eq. (12) to capture the distribution of exposure of items. Note that we re-initialize the ψ and Ψ in each iteration; (iii) updating parameters θ of $\mathcal{G}$ via Eq. (14) to mitigate fairness disparity. After training these three phases a specific number of steps, the model outputs the $\mathcal{G}$'s parameters θ eventually. The overall algorithm is shown in Algorithm 1. Through such mutual learning process, *FairGAN* is able to optimize fairness while maintaining utility as high as possible. Note that, instead of GANs, the first two phases can be implemented using other machine learning models like deep neural networks. The reason that *FairGAN* applies GANs as the techniques to achieve the proposed goals is that GANs is cutting-edge technology and has gained a big success in recommender systems.

5 EMPIRICAL EVALUATION

5.1 Experiment Settings

Datasets. We conducted the experiments on four real-world Amazon datasets [24], which have been commonly used in recommendation systems. 1) *Toys and Games* includes 2,252,771 interactions from 1,342,911 users on 327,698 items; 2) *Beauty* includes 2,023,070 interactions between 1,210,271 users and 249,274 items; 3) *Office Products* contains 1,243,186 interactions between 909,314 users and 130,006 items; and 4) *Digital Music* collects 836,006 feedback between 478,235 users and 266,414 items. Following [11, 26, 36], we regard all interactions as value 1. All datasets are processed by filtering out users and items with less than 10 interactions. We use 80% of interactions as training data set and the others as test data set. Then, we set aside 20% of the training data set as validation data for tuning hyper-parameters. All experiments are carried out by 5-fold cross-validation and the average of results on test data set is reported.

Utility-focused Baselines. We compare with 5 state-of-the-art utility-focused baselines: (i) **BPR** [36] is a pairwise method for Top-k recommendations based on implicit feedback using *sampling-based* learning strategy; (ii) **CFGAN** [11] is an GANs-based approach for Top-k recommendation based on *sampling-based* learning strategy, which employs the vector-wise adversarial learning to provide high recommendation quality; (iii) **CDAE** [46] uses *sampling-based* learning strategy to learn the latent representations of corrupted user-item preferences by Denoising Auto-Encoder; (iv) **ENMF** [14] is a neural based matrix factorization model for Top-k recommendations by efficiently learning parameters from the whole training data without sampling; (v) **IRGAN** [42] is an GANs-based method consisting of a generator that learns the relevance distribution over items via the signals from the discriminator, and a discriminator exploiting the unlabelled data selected by the generator.

Fairness-focused Baselines. We compare with the state-of-the-art fairness models in CF: (i) **FairRec** [34] is a post-processing method to re-rank recommendations based on the predicted relevance scores to guarantee a minimum exposure for each item. The predictions of above five utility-focused baselines (called base rankers) are fed to FairRec for re-ranking, the re-ranked recommendation lists are denoted as **FairRec-BPR**, **FairRec-CDAE**, **FairRec-CFGAN**, **FairRec-ENMF** and **FairRec-IRGAN** respectively as fairness baselines. (ii) **Reg** [35, 49, 50] is commonly used for minimizing disparity between items in recommendation models, which penalizes the disparity by a regularization. In this baseline, we test it by the ranker in *FairGAN* with a regularization term for minimizing exposure disparity between items. Due to the exposure defined in Eq. (5) is non-differential for directly updating the parameters of the ranker in *FairGAN*, we follow [50] to minimize exposure disparity by rewriting Eq. (5) to top-one-probability [10] of item v:

$$P(v|\pi_n) = \frac{1}{m} \sum_{u \in \mathcal{U}} \frac{\exp(\mathcal{G}(v|\mathbf{c}^{\mathbf{u}}))}{\sum_{v' \in \mathcal{I}} \exp(\mathcal{G}(v'|\mathbf{c}^{\mathbf{u}}))}, \tag{15}$$

where $\mathcal{G}(v'|\mathbf{c}^{\mathbf{u}})$ is the predicted relevance score of item v to user u by $\mathcal{G}$. The regularization term for minimizing individual exposure disparity is:

$$\text{Regularization} = \eta \cdot \frac{\sum_{v, v' \in \mathcal{I}} |P(v|\pi_n) - P(v'|\pi_n)|}{2n \sum_{v''} P(v''|\pi_n)}, \tag{16}$$

where η is a tunable parameter for trade-off between utility users gained and fairness. We test it in [5, 10, 15, 20, 25, 30, 35, 40]. Similarly, for fair comparison, we reduce the unfairness of **Reg** to the same level as *FairGAN* when comparing the recommendation quality. We set η to 15 for *Toys & Games* and *Beauty*, 10 and 35 for

Models	Toys and Games								Beauty							
	P@5	P@10	R@5	R@10	G@5	G@10	IED@5	IED@10	P@5	P@10	R@5	R@10	G@5	G@10	IED@5	IED@10
BPR	3.397	2.735	3.615	5.827	4.217	4.830	68.961	62.299	11.230	9.053	12.448	19.552	14.095	16.247	80.054	73.629
CDAE	3.436	2.922	3.672	6.278	4.230	5.031	92.453	89.250	10.306	7.364	12.348	17.410	13.511	14.881	64.987	58.184
CFGAN	3.408	2.785	3.297	5.715	4.075	4.743	98.395	97.345	11.567	9.445	12.405	19.636	14.418	16.605	91.466	87.774
ENMF	3.438	2.814	3.629	6.114	4.392	5.074	80.817	76.061	11.095	8.953	12.626	19.743	14.328	16.589	83.916	77.539
IRGAN	3.407	2.743	3.683	5.965	4.053	4.731	85.151	81.404	10.332	8.416	11.868	18.813	13.018	15.261	89.494	84.527
***FairGAN*-1**	**3.719**	**2.963**	**4.237**	**6.728**	**4.793**	**5.497**	**45.986**	**38.016**	**13.000**	**10.018**	**14.394**	**21.471**	**16.934**	**18.907**	**51.037**	**42.731**
FairRec-BPR	3.036	2.539	3.360	5.532	3.487	4.190	40.743	38.002	10.409	8.475	11.520	18.330	12.355	14.533	54.130	50.296
FairRec-CDAE	3.001	2.636	3.165	5.641	3.354	4.319	50.396	46.708	10.334	7.394	12.401	17.504	13.604	14.973	64.494	56.169
FairRec-CFGAN	3.140	**2.767**	3.037	5.520	3.401	4.343	81.123	91.142	10.507	8.761	11.342	18.383	12.037	14.530	63.059	61.457
FairRec-ENMF	3.149	2.519	3.335	5.465	3.573	4.127	45.363	42.409	9.564	7.985	10.970	17.612	11.386	14.057	43.444	41.215
FairRec-IRGAN	3.036	2.612	3.281	5.778	3.353	4.405	59.062	55.919	10.090	8.400	11.515	18.666	12.020	14.520	72.157	70.399
Reg	2.169	1.705	2.373	3.722	2.822	3.183	38.065	29.863	9.412	7.358	10.665	16.156	12.106	13.743	47.160	39.306
***FairGAN*-2**	**3.419**	2.659	**3.936**	**5.920**	**4.488**	**5.033**	37.185	28.655	**12.263**	**9.158**	**13.850**	**19.853**	**16.088**	**17.646**	41.858	33.759
***FairGAN*-3**	3.207	2.495	3.612	5.645	4.206	4.719	**34.916**	**26.788**	11.383	8.404	13.026	18.652	15.110	16.538	**39.365**	**31.985**

Models	Office Products								Digital Music							
	P@5	P@10	R@5	R@10	G@5	G@10	IED@5	IED@10	P@5	P@10	R@5	R@10	G@5	G@10	IED@5	IED@10
BPR	4.246	3.691	5.186	8.972	5.424	6.803	85.521	81.932	11.563	8.964	15.015	22.506	16.227	18.634	73.671	66.710
CDAE	3.868	2.992	4.577	7.072	5.197	5.933	88.130	78.514	12.120	9.171	15.824	23.184	17.088	19.366	73.242	66.588
CFGAN	4.933	4.029	5.817	9.555	6.214	7.483	94.534	92.913	12.509	9.516	16.513	24.265	17.698	20.138	73.107	66.426
ENMF	4.320	3.708	5.191	8.836	5.549	6.859	89.530	86.619	12.431	9.495	16.399	24.022	17.693	20.078	81.652	75.952
IRGAN	4.319	3.634	5.189	8.921	5.441	6.750	91.389	89.312	10.428	8.222	13.508	20.688	14.577	16.874	90.381	86.934
***FairGAN*-1**	**5.167**	**4.112**	**6.405**	**10.260**	**6.838**	**8.088**	**71.521**	**66.015**	**13.326**	**10.040**	**17.174**	**25.208**	**18.990**	**21.447**	**63.831**	**55.168**
FairRec-BPR	3.704	3.352	4.667	8.130	4.315	5.480	65.376	63.505	10.715	8.582	13.962	21.487	13.358	16.417	43.360	42.758
FairRec-CDAE	3.939	3.026	4.699	7.218	5.237	5.937	82.576	73.507	11.950	9.091	15.609	22.966	16.704	18.941	72.910	66.061
FairRec-CFGAN	3.870	3.296	4.679	8.002	4.239	5.475	48.520	48.074	11.813	9.220	15.496	**23.563**	15.138	18.159	56.505	53.927
FairRec-ENMF	3.484	2.980	4.232	7.353	3.892	5.029	46.800	46.178	11.089	8.871	14.634	22.475	13.512	16.673	45.543	41.965
FairRec-IRGAN	4.101	3.543	4.945	8.711	4.742	6.074	78.711	78.321	10.368	8.227	13.242	20.662	13.436	15.907	80.894	79.121
Reg	3.041	2.447	3.754	5.922	4.093	4.820	42.175	34.330	6.526	4.349	8.993	11.431	10.225	10.752	45.212	34.570
***FairGAN*-2**	**4.636**	**3.754**	**5.661**	**9.058**	**6.257**	**7.390**	58.223	51.627	**12.088**	**9.230**	**15.753**	22.950	**17.452**	**19.723**	46.774	37.192
***FairGAN*-3**	3.894	3.000	4.672	7.252	5.272	6.038	**41.483**	**34.041**	11.658	8.641	15.207	21.613	16.800	18.727	**42.755**	**33.080**

Table 1: Recommendation quality ($P@k$, $R@k$, and $G@k$) and fairness ($IED@k$) in percentage (%) on four real world datasets (k = 5 and 10, the number of items recommended). The best results are bold-faced.

Office Products and *Digital Music* after fixing other optimal hyper-parameters of $\mathcal{G}$.

Metrics. We employ common Top-k ($k \leqslant n$) ranking metrics to evaluate recommendation quality, including Precision ($P@k$), Recall ($R@k$), and Normalized Discounted Cumulative Gain ($G@k$). The fairness metric $IED@k$, i.e., Individual Exposure Disparity of rankings π_k defined in Eq. (7). The larger $P@k$, $R@k$ and $G@k$ indicate the better recommendation quality while the smaller $IED@k$ means the fairer recommendations.

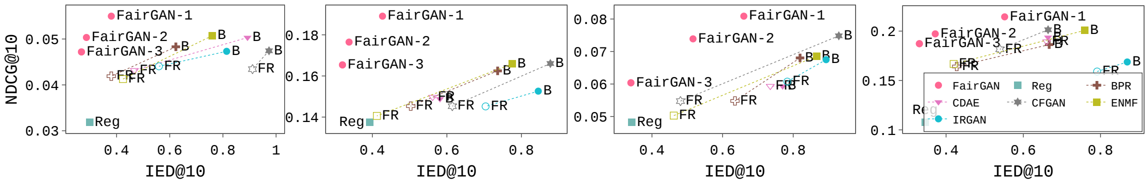
Parameters Setting. Our *FairGAN* is implemented with TensorFlow[1], which is an open-source software library for deep learning. All hyper-parameters are tuned according to results of validation data. The parameters for all baseline methods are tuned to achieve optimal performances after initializing them as the settings in the original papers. For reproducibility, all source codes of this work has been released publicly[2] and the details of parameters settings are described in the Appendix. We set *FairGAN* at different levels of fairness controlled by parameter α in Eq. (14), denoted as ***FairGAN*-1**, ***FairGAN*-2**, and ***FairGAN*-3** respectively. ***FairGAN*-1** with a smaller α aims to prove the *fairness-aware learning strategy* of *FairGAN* is effective to search the space of optimal rankings that can maximize user utility while retaining fairness. Due to the performance difference of FairRec on different base rankers, ***FairGAN*-2** and ***FairGAN*-3** are set different larger α to fairly compare with fairness-focused baselines FairRec and Reg, we make ***FairGAN*-2** or ***FairGAN*-3** to have the same level of performance on fairness with baselines and then compare the recommendation quality.

[1]https://www.tensorflow.org
[2]https://github.com/jasonshere/FairGAN

5.2 Comparison with Baselines

Comparison with Utility-focused Baselines: The results are shown in Table 1. The two-tailed, paired t-test with a 99% (95%) confidence level indicates that *FairGAN*-1 significantly outperforms the state-of-the-art utility-focused baselines on recommendation quality (fairness with a slightly higher p-value 0.061 on *Digital Music*) on all datasets. Specifically, *FairGAN*-1 exhibits average improvement 9.62%, 12.52%, 7.07% and 5.62% on recommendation quality and 36.15%, 24.02%, 17.90% and 14.82% on fairness on four datasets respectively. This demonstrates the effectiveness of the proposed *fairness-aware learning strategy* on capturing user preference from a fairness-aware searching space without treating unobserved interactions as negative. Interestingly, we notice that slightly improving fairness can promote unpopular items without influencing the original high rankings of popular items; therefore, the recommendation quality can be further improved. More importantly, the better fairness of *FairGAN* verifies the capability of the controller on resolving the issue of non-differential optimization.

Comparison with Fairness-focused Baselines: We then compare *FairGAN*-2 and *FairGAN*-3 with FairRec and Reg. As shown in the results, FairRec can effectively reduce *IED* of predictions from base rankers, which generally performs better on fairness improvements when using ENMF (decreases IED@5 by 46.012%, and IED@10 by 45.631% on average) as the base ranker than using others. However, the fairness improvements for CDAE are little (drops IED@5 by 13.251%, and IED@10 by 14.574% on average). This discloses the performance of FairRec is highly coupled to base rankers, while *FairGAN* is independent of any other recommendation models, being able to dynamically search the space of fair optimal rankings that can maximize rankings utility. In the results,



(a) Toys and Games (b) Beauty (c) Office Products (d) Digital Music

Figure 2: *NDCG*@10 **and** *IED*@10 **of all models.** *B* **indicates the results of utility-focused baselines and** *FR* **indicates the results of FairRec. Pink dots indicate the results of the proposed** ***FairGAN*.**

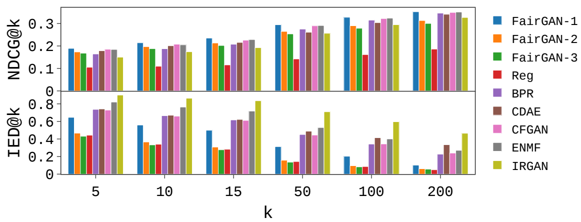


Figure 3: *NDCG*@*k* **and** *IED*@*k* **of** ***FairGAN*** **and baselines on Digital Music.**

Reg is able to effectively improve exposure-based fairness by rewriting exposure definition as top-one-probability [50]. However, Reg sacrifices much more recommendation quality than *FairGAN* when having the same level of fairness.

FairGAN-3 outperforms the best FairRec baseline, FairRec-ENMF, on both recommendation quality (average improvement 6.549%, 13.662%, 10.351% and 5.423% on four datasets respectively) and fairness (average improvement 44.117%, 19.609%, 24.236%, 16.690% on four datasets respectively). *FairGAN*-3 also performs better than Reg on both recommendation quality and fairness, where the average improvement on recommendation quality is 32.975%, 16.342%, 20.144%, 43.898% respectively on four datasets, and the average enhancement on fairness is 10.248%, 21.345%, 1.258%, 5.125% respectively. When having the same level of performance on one side (either recommendation quality or fairness) as FairRec-*, *FairGAN*-2 performs much better on the other side.

To better illustrate the performance of all models on both recommendation quality and fairness, we plot *NDCG*@10 and *IED*@10 results of all models in Fig. (2), where x-axis is *IED*@10 and y-axis is *NDCG*@10. *B* indicates the results of utility-focused baselines and *FR* indicates that of FairRec baselines, and *Reg* is the results of baseline Reg. The results show that *FairGAN* (pink dots) are normally in top left corner, which represents the better recommendation quality and fairness compared with baselines on four datasets.

Performance on Different k**:** The comparisons between *FairGAN* and baselines on *NDCG* and *IED* at different k settings, $[5, 10, 15, 50, 100, 200]$, are reported. Due to page limit, we only present the experimental results on *Digital Music* in Fig. (3), but the similar trends have been observed on other datasets. Note we do not compare with FairRec here since FairRec has high computation complexity on re-ranking the recommendation lists with large k. The results show that *FairGAN*-1 outperforms all utility-based baselines on both *NDCG* and *IED* at all k settings. This indicates *FairGAN* is capable of optimizing fairness at all possible k by running once while maintaining the high utility, which is distinct from FairRec that needs to run multiple times for optimizing fairness, each for one k setting. *FairGAN*-2 and *FairGAN*-3 perform similarly on

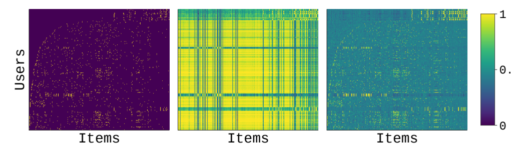


Figure 4: Data Visualization on ***Beauty*.**

fairness with Reg, but Reg sacrifices much more recommendation quality than *FairGAN*-2 and *FairGAN*-3, regardless the k setting.

5.3 Ablation Analysis

We conduct ablation analysis on each component of *FairGAN*. We denote $\underline{R}$ as the ranker, $\underline{C}$ as the controller, and $\underline{A}$ as the process of adapting the ranker in *Phase 3*. We use "+" (or "−") to indicate a component included (or excluded) in *FairGAN*. We test five different settings: **(i)** *FairGAN*-$\underline{R}^-\underline{C}^-\underline{A}^-$: no components are trained during training, i.e., all three phases in *FairGAN* are not executed; **(ii)** *FairGAN*-$\underline{R}^+\underline{C}^-\underline{A}^-$: only is the ranker $\underline{R}$ trained, i.e., only *Phase 1* is executed; **(iii)** *FairGAN*-$\underline{R}^+\underline{C}^+\underline{A}^-$: only exclude the process of adapting the ranker in *Phase 3* **(iv)** *FairGAN*-$\underline{R}^+\underline{C}^-\underline{A}^+$: only is the controller $\underline{C}$ not trained (*Phase 2* is not executed); **(v)** *FairGAN*-$\underline{R}^-\underline{C}^+\underline{A}^+$: only is the ranker not trained (*Phase 1* is not executed).

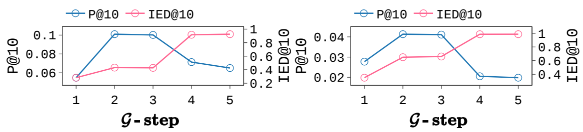
From the results in Table 2, the observations can be made: (i) *FairGAN*-$\underline{R}^-\underline{C}^+\underline{A}^+$ outperforms *FairGAN*-$\underline{R}^-\underline{C}^-\underline{A}^-$ on fairness. It verifies the controller $\underline{C}$ is able to effectively minimize individual exposure disparity. (ii) *FairGAN*-1 performs much better than *FairGAN*-$\underline{R}^+\underline{C}^-\underline{A}^-$ on all measure metrics. It implies the effectiveness of the *fairness signals* generated by the controller $\underline{C}$ on searching fair rankings with high utility. (iii) *FairGAN*-$\underline{R}^+\underline{C}^+\underline{A}^-$ has the same performance as *FairGAN*-$\underline{R}^+\underline{C}^-\underline{A}^-$ but much worse than *FairGAN*-1. It evidences the process of adapting the ranker (*Phase 3*) is indispensable. (iv) *FairGAN*-$\underline{R}^-\underline{C}^-\underline{A}^-$ and *FairGAN*-$\underline{R}^-\underline{C}^+\underline{A}^+$ perform much worse than *FairGAN*-1 on recommendation quality. It reveals the ranker $\underline{R}$ is necessary in *FairGAN* to capture the real distribution of interactions; (v) *FairGAN*-$\underline{R}^+\underline{C}^-\underline{A}^+$ performs worse than *FairGAN*-1 on all measure metrics. It discloses that the effectiveness of the controller $\underline{C}$ on capturing the distribution of exposure based on current rankings generated by $\underline{R}$. In short, we conclude all components ($\underline{R}$, $\underline{C}$, $\underline{A}$) of *FairGAN* are essential for achieving the optimal performance in terms of recommendation quality and fairness.

To further investigate the components of *FairGAN*, we also visualize the training set of *Beauty* (Fig. (4) (left)), the output of *FairGAN*-$\underline{R}^+\underline{C}^-\underline{A}^-$ (Fig. (4) (center)), and the output of *FairGAN*-1 (Fig. (4) (right)). In Fig. (4) (left), the yellow dots represent observed interactions and the rest represents the unobserved interactions (dark purples). Fig. (4) (center) demonstrates that training the ranker

Models	Toys and Games P@5	P@10	R@5	R@10	G@5	G@10	IED@5	IED@10	Beauty P@5	P@10	R@5	R@10	G@5	G@10	IED@5	IED@10
***FairGAN*-$\underline{R}^{-}\underline{C}^{-}\underline{A}^{-}$**	0.440	0.469	0.492	1.204	0.517	0.783	36.411	30.222	0.579	0.604	0.619	1.285	0.645	0.910	38.575	33.839
***FairGAN*-$\underline{R}^{+}\underline{C}^{-}\underline{A}^{-}$**	2.027	1.759	2.362	4.230	2.525	3.202	97.803	96.487	8.702	6.771	10.760	16.378	11.369	13.194	95.211	92.383
***FairGAN*-$\underline{R}^{+}\underline{C}^{+}\underline{A}^{-}$**	2.027	1.759	2.362	4.230	2.525	3.202	97.803	96.487	8.702	6.771	10.760	16.378	11.369	13.194	95.211	92.383
***FairGAN*-$\underline{R}^{+}\underline{C}^{-}\underline{A}^{+}$**	2.203	1.869	2.565	4.471	2.823	3.468	97.157	95.926	8.000	6.342	9.846	15.008	10.599	12.365	95.249	93.284
***FairGAN*-$\underline{R}^{-}\underline{C}^{+}\underline{A}^{+}$**	0.495	0.432	0.541	0.931	0.592	0.732	**26.988**	**20.323**	0.630	0.608	0.735	1.321	0.816	1.031	**24.179**	**19.105**
***FairGAN*-1**	**3.719**	**2.963**	**4.237**	**6.728**	**4.793**	**5.497**	45.986	38.016	**13.000**	**10.018**	**14.394**	**21.471**	**16.934**	**18.907**	51.037	42.731

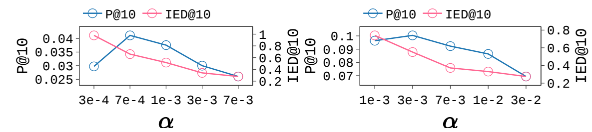
Models	Office Products P@5	P@10	R@5	R@10	G@5	G@10	IED@5	IED@10	Digital Music P@5	P@10	R@5	R@10	G@5	G@10	IED@5	IED@10
***FairGAN*-$\underline{R}^{-}\underline{C}^{-}\underline{A}^{-}$**	0.672	0.600	0.854	1.501	0.819	1.076	36.067	31.515	0.368	0.409	0.347	0.839	0.430	0.624	39.049	33.183
***FairGAN*-$\underline{R}^{+}\underline{C}^{-}\underline{A}^{-}$**	2.898	2.706	3.722	6.855	3.796	5.061	98.906	98.198	9.141	7.056	12.684	18.803	13.219	15.289	95.280	93.308
***FairGAN*-$\underline{R}^{+}\underline{C}^{+}\underline{A}^{-}$**	2.898	2.706	3.722	6.855	3.796	5.061	98.906	98.198	9.141	7.056	12.684	18.803	13.219	15.289	95.280	93.308
***FairGAN*-$\underline{R}^{+}\underline{C}^{-}\underline{A}^{+}$**	3.061	2.816	4.043	7.174	4.048	5.315	98.745	98.000	10.284	7.805	14.246	20.531	15.105	17.120	91.874	89.110
***FairGAN*-$\underline{R}^{-}\underline{C}^{+}\underline{A}^{+}$**	0.436	0.499	0.559	1.279	0.532	0.840	**22.064**	**16.866**	0.566	0.479	0.650	1.043	0.675	0.807	**27.813**	**21.296**
***FairGAN*-1**	**5.167**	**4.112**	**6.405**	**10.260**	**6.838**	**8.088**	71.521	66.015	**13.326**	**10.040**	**17.174**	**25.208**	**18.990**	**21.447**	63.831	55.168

Table 2: Ablation Analysis (the best results are bold-faced). $\underline{R}$ indicates the ranker and $\underline{C}$ indicates the controller; $\underline{A}$ is denoted as the process of adapting $\underline{R}$ in *Phase 3*. + and − indicate that the corresponding component is trained or not.



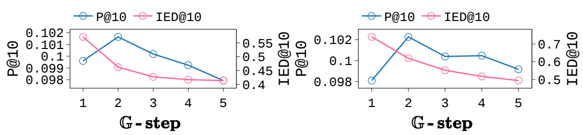
(a) Beauty **(b) Office Products**

Figure 5: Impact of $\mathcal{G}$-step on Beauty and Office Products.



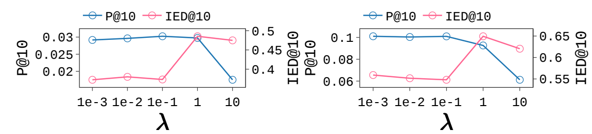
(a) Office Products **(b) Digital Music**

Figure 7: Impact of α on Office Products and Digital Music.



(a) Beauty **(b) Digital Music**

Figure 6: Impact of $\mathbb{G}$-step on Beauty and Digital Music.



(a) Toys and Games **(b) Digital Music**

Figure 8: Impact of λ on Toys and Games, and Digital Music.

only on observed interactions leads the model to predict all interactions (observed and unobserved) as 1, thus failing to capture the real distribution of interactions. In Fig. (4) (right), the output of *FairGAN*-1 is highly similar to the data distribution in Fig. (4) (left). It proves the effectiveness of the controller on driving the ranker to search the space of optimal rankings so that the real distribution of interactions can be captured as much as possible.

5.4 Impact of Hyper-Parameters

Impact of $\mathcal{G}$-step. We vary $\mathcal{G}$-step, the number of steps for training the generator $\mathcal{G}$ of the ranker, to be $[1, 2, 3, 4, 5]$ respectively while fixing other parameters.The results of *Precision*@10 and *IED*@10 on *Beauty* and *Office Products* are shown in Fig. (5). The results demonstrate that the larger step number in each iteration, the *IED* increases more, i.e., unfairer exposure between items; however, the recommendation quality gets increased first and then dropped. The best $\mathcal{G}$-step for recommendation quality is 2 and 3.

Impact of $\mathbb{G}$-step. We vary $\mathbb{G}$-step, the number of steps for training the generator $\mathbb{G}$ of the controller, to be $[1, 2, 3, 4, 5]$ respectively. The results of *Precision*@10 and *IED*@10 on *Beauty* and *Digital Music* in Fig. (6). The results show that the more step number in each iteration, *IED* reduces more and decrease rate weakens at around 4 and 5. For the recommendation quality, *Precision*@10 reaches the highest value at around 2 and then starts to drop.

Impact of α. We vary the trade-off parameter α in Eq. (14) (as shown in Fig. (7). Specifically, α is set at [3e-4, 7e-4, 1e-3, 3e-3, 7e-3] for *Office Products* and [1e-3, 3e-3, 7e-3, 1e-2, 3e-2] for *Digital Music*. Similar to the impact of $\mathbb{G}$-step, the larger α contributes more on minimizing *IED*. The trend of recommendation quality is also similar to that of $\mathbb{G}$-step, i.e., increases first and then decreases. The potential reason for better recommendation quality at second setting is that slightly promoting unpopular items almost do not affect the original high rankings of popular items. However, larger values will promote more unpopular items and decrease the exposure of popular items, thus damaging the recommendation quality.

Impact of λ. Finally, we investigate the impact of the gradient penalty coefficient λ in Eq. (9) and Eq. (12). We vary its value at $[0.001, 0.01, 0.1, 1, 10]$ respectively over four datasets. The results of *Precision*@10 and *IED*@10 reported in Fig. (8) indicate that both recommendation quality and fairness are stable under smaller λ ($\lambda \leqslant 0.1$). Meanwhile the larger λ ($\lambda > 0.1$) leads to the lower recommendation quality and fairness.

6 CONCLUSION AND FUTURE WORK

This paper proposes a WGANs-GP based learning algorithm, called *FairGAN* mapping the fairness issues in recommendations to the problem of lacking negative feedback in implicit feedback data. The proposed *FairGAN* consisting of a ranker and a controller applies a novel *fairness-aware learning strategy* that only adopts the positive feedback in implicit feedback data and does not explicitly treat unobserved interactions as negative. The *FairGAN* generates *fairness signals* to search the optimal rankings that can fairly allocate exposure to users while maintaining user utility as high as possible. Finally, extensive experiments show the effectiveness of the proposed algorithm over the state-of-the-art baselines.

In our future work, we are interested in investigating the issues of fairness across users, which are also important for recommendations. We are also interested in exploring the way to improve items fairness and users fairness simultaneously.

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A APPENDICES

A.1 Algorithm 1

The overall process of training *FairGAN* is detailed in Algorithm 1.

Algorithm 1 *FairGAN*

Input: $\mathbb{R}$, c, learning rate $lr^{\mathcal{G}}$, $lr^{\mathcal{D}}$, $lr^{\mathbb{G}}$ and $lr^{\mathbb{D}}$ for $\mathcal{G}$, $\mathcal{D}$, $\mathbb{G}$ and $\mathbb{D}$, number of epochs N
Output: $\mathcal{G}$'s parameters θ
Initialize θ, Θ, ψ and Ψ
Initialize epoch $\leftarrow 0$
while epoch $\leqslant N$ **do**
  Sample minibatch of users $\mathcal{B}$
  /* The following user u belongs to the users batch $\mathcal{B}$ */

  /* **Phase 1: Training Ranker** */
  for $\mathcal{D}$-step **do**
    Get real purchase vectors $\mathbf{r^u} \sim \mathbb{R}$
    Generate fake purchase vectors $\mathbf{\hat{r}^u} \sim \mathcal{G}$
    Update $\mathcal{D}$ according to Eq. (9).
  end for
  for $\mathcal{G}$-step **do**
    Generate fake purchase vectors $\mathbf{\hat{r}^u} \sim \mathcal{G}$
    Update $\mathcal{G}$ according to Eq. (10).
  end for

  /* **Phase 2: Training Controller** */
  Re-initialize ψ and Ψ
  for $\mathbb{D}$-step **do**
    Generate fake purchase vectors $\mathbf{\hat{r}^u} \sim \mathcal{G}$
    Compute real exposure vectors $\mathbf{e^u}$ based on $\mathbf{\hat{r}^u} \sim \mathcal{G}$
    Generate fake exposure vectors $\mathbf{\hat{e}^u} \sim \mathbb{G}$
    Update $\mathbb{D}$ according to Eq. (12).
  end for
  for $\mathbb{G}$-step **do**
    Generate fake purchase vectors $\mathbf{\hat{r}^u} \sim \mathcal{G}$
    Compute real exposure vectors $\mathbf{e^u}$ based on $\mathbf{\hat{r}^u} \sim \mathcal{G}$
    Generate fake exposure vectors $\mathbf{\hat{e}^u} \sim \mathbb{G}$
    Update $\mathbb{G}$ according to Eq. (13).
  end for

  /* **Phase 3: Controlling Fairness** */
  for $\mathcal{F}$-step **do**
    Generate fake purchase vectors $\mathbf{\hat{r}^u} \sim \mathcal{G}$
    Generate fake exposure vectors $\mathbf{\hat{e}^u} \sim \mathbb{G}$
    Fix $\mathbb{G}$ and Update $\mathcal{G}$ according to Eq. (14).
  end for
  epoch $\leftarrow$ epoch + 1
end while
return $\mathcal{G}$

A.2 Details of Parameters Setting

The learning rate for all models are tuned between [1e-6, 1e-5, 1e-4, 1e-3, 1e-2, 1e-1]. The dropout percentage and l_2-resularizers for avoiding overfitting are tuned between [0, 0.1, 0.3, 0.5, 0.7] and [1e-4, 1e-3, 1e-2, 1e-1] respectively, the size of mini-batch is tested in [32, 64, 128, 256, 512, 1024]. For sampling-based methods, the number or ratio of negative samples is tuned between [1, 2, 3, 4, 5, 6] (BPR, CDAE, IRGAN) or [0.1, 0.3, 0.5, 0.7, 0.9] (CFGAN). For ENMF, the weight of missing data is tuned amongst [0.005, 0.01, 0.05, 0.1, 0.2, 0.5, 1]. For factorization-based methods, the dimension of latent factors is tuned amongst [10, 20, 30, 40, 50, 100].

For our proposed algorithm *FairGAN*, we use Glorot normal initialization approach [20] to initialize layers of neural networks, the activation functions of hidden layers are tuned between [tanh, relu, elu, sigmoid, softmax], the number of hidden layers is tuned from 1 to 3, and the number of units per hidden layer is tuned between [50, 100, 500, 1000, 5000, 10000, 12000]. The penalty coefficient λ for learning $\mathcal{D}$ and $\mathbb{D}$ is tuned between [0.001, 0.01, 0.1, 1, 10]. The number of steps for learning $\mathcal{G}$ and $\mathbb{G}$ is tuned from 1 to 5 while fixing the steps for training discriminators to 1. For the trade-off parameter α in Eq. (14), we tune it for different datasets amongst different ranges after fixing the number of steps for adapting the ranker in *Phase 3* to 3, where [5e-4, 1e-3, 5e-3, 1e-2, 5e-2] is tuned for *Toys and Games*, [5e-3, 1e-2, 5e-2, 1e-1, 5e-1] is tested for *Beauty*, [3e-4, 7e-4, 1e-3, 3e-3, 7e-3] is tested for *Office Products* and [1e-3, 3e-3, 7e-3, 1e-2, 3e-2] for *Digital Music*. The impact of parameters will be discussed in Section 5.4. After the tuning progress, *tanh* is used as the activation of hidden layers in $\mathcal{G}$ and $\mathcal{D}$, and *relu* is set for $\mathbb{G}$ and $\mathbb{D}$. The size of output layer units of discriminators is set to 1, which is activated with *sigmoid* function. The size of output vector of generators is set as n. For $\mathcal{G}$, the activation of output layer is *tanh*, while *softmax* is set for $\mathbb{G}$'s output layer. Similar to CFGAN [11], the user-specific condition vector $\mathbf{c^u}$ is the purchase history vector of user u. The penalty coefficient λ of discriminators is set to 0.01. The number of steps for training $\mathcal{G}$ and $\mathbb{G}$ is set to 3 finally.